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ABSTRACT

This paper estimates the contribution of human capital to the Black-white earnings gap in three separate samples of men spanning from 1966 through 2017, using both educational attainment and performance on standardized tests to measure human capital. There are three main findings. First, the magnitude of reductions in the Black-white earnings gap that occur after controlling for human capital has become much larger over time, suggesting a growing contribution of human capital to Black-white earnings disparities. Second, these increases are almost entirely due to growth in the returns to human capital, which magnify the impact of any racial differences in human capital levels, rather than to increasing racial gaps in the human capital traits themselves. Finally, growth in the explanatory power of human capital has been primarily due to increases in the association between human capital and the likelihood of nonwork, with no clear increases in the extent to which human capital explains Black-white wage differences. These findings highlight how apparently race-neutral structural developments in the U.S. labor market, such as increasing skill prices and falling labor force participation rates among less-skilled men, have had large impacts on racial inequity.

JEL Classification Codes: J15, J24, J31, J71

Key Words: human capital, earnings gap, racial gap, black-white, NLS, decomposition

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Human Capital and Black-White Earnings Gaps, 1966 - 2017

Owen Thompson*

Abstract

This paper estimates the contribution of human capital to the Black-white earnings gap in three separate samples of men spanning from 1966 through 2017, using both educational attainment and performance on standardized tests to measure human capital. There are three main findings. First, the magnitude of reductions in the Black-white earnings gap that occur after controlling for human capital has become much larger over time, suggesting a growing contribution of human capital to Black-white earnings disparities. Second, these increases are almost entirely due to growth in the *returns* to human capital, which magnify the impact of any racial differences in human capital levels, rather than to increasing racial gaps in the human capital traits themselves. Finally, growth in the explanatory power of human capital has been primarily due to increases in the association between human capital and the likelihood of nonwork, with no clear increases in the extent to which human capital explains Black-white wage differences. These findings highlight how apparently race-neutral structural developments in the U.S. labor market, such as increasing skill prices and falling labor force participation rates among less-skilled men, have had large impacts on racial inequity.

*Williams College and NBER. I thank the Upjohn Institute for Employment Research for generous financial support and seminar participants at Amherst College and the University of Notre Dame for helpful comments.

Introduction

Large disparities in the wages and earnings of African Americans and whites have existed for as long as data on labor market outcomes have been collected, and such disparities remain one of the defining social and economic issues of the United States (Myrdal 1962; Altonji & Blank 1999).

Among the many explanations for these disparities that have been advanced by researchers and policy actors, a fundamental distinction can be drawn between explanations that emphasize differences in the human capital levels of Blacks and whites versus explanations that emphasize differential treatment in the labor market among similarly qualified individuals of different races. One reason this distinction is important is that it has direct policy implications. If earnings disparities are primarily due to human capital disparities, then policies that promote human capital acquisition among minorities would also reduce earnings gaps. In contrast, if human capital is not the primary driver of Black-white earnings gaps, then policies that expand or more vigorously enforce antidiscrimination laws are more likely to be effective. Even more fundamentally, the distinction between explanations for racial inequality that emphasize human capital versus those that do not is important because asserting a dominant role for human capital implicitly or explicitly assigns responsibility for closing earnings gaps to Black Americans themselves, who are encouraged to increase their investments in human capital, perhaps with some assistance from public education systems or other policy supports, rather than placing responsibility on more structural aspects of the labor market.

This paper provides a comprehensive analysis of human capital's contribution to racial earnings disparities from the period following implementation of the 1964 Civil Rights Act through the present. Using three nationally representative samples of men with information on both formal schooling and standardized test performance, I find that differences in the human capital levels of Blacks and whites "explain" a large and increasing share of Black-white earnings disparities: controlling for human capital reduces Black-white differences in total earnings by approximately 10 percent in data from the late 1960s and the 1970s, by approximately 20 percent in data from the 1980s and 1990s, and by approximately 30 percent in data from the 2000s and 2010s. However, while the overall contribution of human capital to racial earnings disparities has unambiguously increased, the precise reasons for these increases are nuanced and perhaps surprising. Two features of the increasing explanatory power of human capital are particularly important for understanding the relationship between human capital and Black-white earnings gaps.

First, the increased explanatory power of educational attainment and standardized test performance is almost wholly due to growth in the earnings premiums associated with these traits, while actual Black-white gaps in human capital characteristics were stable or modestly falling over the study period. Increases in skill premia starting in the late twentieth century are well established, and the current paper's findings highlight that in the presence of these rising skill premia, increases in the relative test scores and educational attainment of Black Americans are not a sufficient condition for reducing the Black-white earnings gaps or the contribution of human capital to the earnings gap.

Second, the increasing importance of human capital is driven almost entirely by the extensive margin between work and nonwork. At intensive margins such as hourly wages and hours worked among employed men, the importance of human capital to Black-white disparities has actually fallen significantly from the 1980s to the present. This finding is closely related to the general phenomenon of declining labor force participation rates among less-skilled men in the past several decades, as well as to increasingly punitive criminal justice policies that have had a highly disproportionate impact on Black men.

These findings contribute to two distinct strands of the extensive existing literature on U.S. racial inequality.

First and most directly is a strand of the literature that estimates the contribution of human capital to racial gaps in labor market outcomes. A canonical study in this area is Neal & Johnson (1996), who find that controlling for standardized test scores eliminates a large share of the Black-white gap in hourly wages. Other important contributions include Lang

& Manove (2011), Ritter & Taylor (2011), Fryer (2011), Gelbach (2016), and Luo (2020). One contribution of the current paper is to build on this literature by providing estimates with a similar basic structure as Neal & Johnson (1996) and subsequent studies but with samples that span a wider range of years and with additional outcome measures such as total earnings and extensive margin outcomes.

Second, and perhaps more important, I contribute to a recent strand of the literature that emphasizes how structural aspects of the labor market can impact racial earnings inequality. For instance, recent work by Bayer & Charles (2018) evaluates how changes in the overall earnings distribution contributed to differences in the earnings of Black and white men between 1940 and the present, with a key finding being that racial earnings inequality at the median has been predominantly determined by earnings trajectories of *all* men in the lower percentiles of the earnings distribution, where Black men are disproportionately concentrated. Another important study in this area is Derenoncourt & Montialoux (2020), who show that a large share of the racial convergence in hourly wages that occurred in the late 1960s and early 1970s can be attributed to minimum wage coverage expansions included in the Fair Labor Standards Act of 1966, which disproportionately benefited African American workers.

These studies are very informative about the evolution of U.S. racial inequality, but as recently argued by James Heckman,[1] there are also inherent limitations to evaluating structural determinants of racial earnings differences without directly analyzing the role of individual skill differences. The current paper therefore attempts to build on this strand of the literature by incorporating more direct and comprehensive human capital measures than other recent work in this area. The incorporation of improved skill measures over a large range of cohorts is especially useful for evaluating how racial inequality among men has been affected by key structural developments in the U.S. labor market, such as rising skill premia (Katz & Murphy 1992; Autor, Katz, & Kearney 2008; Goldin & Katz 2009) and falling male labor force participation rates (Autor & Duggan 2003; Krueger 2017; Aguiar et al. 2017).

[1] See http://www.kaltura.com/tiny/vzwoa (retrieved 12/18/2020).

1 Data and Measures

The analysis uses three separate nationally representative longitudinal samples, all of which contain detailed information on earnings, educational attainment, and standardized test scores. This section describes these samples and the key variables used in the analysis.

1.1 Samples

The first data set is the National Longitudinal Survey's Original Cohort of Young Men (NLS-OC). The NLS-OC contains a large set of socioeconomic and demographic variables for a nationally representative sample of 5,225 men who were born between 1941 and 1952 and were interviewed 12 times between 1966 and 1981.

The second data set is the 1979 National Longitudinal Survey of Youth (NLSY-79), which includes 6,403 male respondents who were born between 1957 and 1964 and have been surveyed on an annual or biannual basis from 1979 through the present.

The third and final data set is the 1997 National Longitudinal Survey of Youth (NLSY-97), whose 4,599 male respondents were born between 1980 and 1984 and have been interviewed annually or biannually from 1997 through the present, with the most recent available wave occurring in 2017. Participants in the NLSY-97 were aged 32–37 in the most recent available wave, and therefore only recently reached an age range at which adult socioeconomic outcomes can be reliably observed.

Of the three surveys, the data from the NLS-OC is unambiguously of the lowest quality. This is true with respect both to certain aspects of the overall sample construction, and to the measurement of some of the key variables, most importantly standardized test scores. The relevant data-quality issues are discussed in detail in Section 1.2, below, and estimates that make various adjustments to the NLS-OC to test whether data limitations are likely to alter the main conclusions are reported in Section 2.3. Overall, these exercises indicate that while the NLS-OC has unambiguous shortcomings, the balance of evidence suggests that the survey still allows for estimates that are both internally credible and generally comparable to the estimates from the other two surveys.

I restrict all three samples to men aged 21–37, and I exclude years in which respondents reported being enrolled in school. The lower bound on age and the exclusion of current students are imposed to help ensure that respondents have substantively entered the labor force at the time of observation, while the upper age bound of 37 is the age of the oldest NLSY-97 respondents in the most recent wave. Previous research has found that earnings observed in this age range are reasonably representative of lifetime earnings (Black & Devereux 2010; Chetty et al. 2017; Mazumder 2018), and below, I show that the paper's main findings are not sensitive to alternative age ranges or to including men currently enrolled in school.[2]

After applying these age restrictions, men from the NLS-OC are observed primarily in the 1970s, men from the NLSY-79 are observed primarily in the mid-1980s through the late 1990s, and men from the NLSY-97 are observed primarily in the mid-2000s through the mid-2010s. The three data sets can therefore jointly provide evidence on the nature of Black-white earnings dynamics throughout the post–Civil Rights period.

1.2 Measures

My preferred earnings measure is the total of all income from wages, salaries, and farm and business income in the previous calendar year, which was reported in all waves of all three surveys, with men who have zero earnings retained. This measure is maximally holistic since it incorporates both wage levels and the probability and intensity of labor force participation. Annual earnings are inflated to 2017 dollars, then transformed using the inverse hyperbolic sine function. This allows for an interpretation of coefficients that is generally similar to when earnings are transformed using the natural logarithm function in most applications, but preserves observations with zero earnings (Burbidge, Magee & Robb 1988; Bellemare &

[2] All three surveys contain oversamples of Blacks and provide sampling weights designed to make the samples nationally representative. I apply these weights in the main analyses, and I demonstrate robustness to not applying sampling weights in Section 2.2. The NLSY-79 originally contained oversamples of military personnel and low-income whites, in addition to racial minorities, but these were discontinued in 1984 and 1990 for budgetary reasons and are excluded here. All three samples are also restricted to non-Hispanic Blacks and whites, and they exclude other racial and ethnic minorities.

Wichman 2020). In Section 2.2, I show that the results are similar if I measure earnings as ln(earnings+1). For expositional convenience, I refer to the inverse hyperbolic sine of earnings as "log earnings." In some specifications, I also use binary measures of positive earnings or respondent's hourly wages as the outcome measure. [3]

Figure 1 plots the Black-white gap in log total earnings in each calendar year for the NLS-OC, NLSY-79, and NLSY-97, and for comparison it also plots comparable estimates from the decennial censuses and ACS. Reassuringly, the levels and trends of the Black-white earnings gap in the longitudinal surveys used here are very similar to those observed in the much larger census and ACS samples. In both sets of data sources, racial disparities in total earnings are large and are increasing over the study period, going from approximately 50 log points in the early 1970s to approximately 200 log points in the 2010s. The large magnitudes of these gaps and their growth over time may seem surprising, but they highlight the impact of including zero-earners when evaluating Black-white earnings gaps.

A unique feature of all three surveys is that they contain credible standardized test-score measures for a large number of participants.

For the NLSY-79 and NLSY-97 samples, I use scores on the Armed Forces Qualification Test (AFQT), which was administered directly by the survey administrators to 93.9 percent of NLSY-79 participants and to 79.3 percent of NLSY-97 participants, and which has been widely used and validated in the economic and psychological literatures. I use AFQT scores that were adjusted for age at the time of testing by survey administrators, and I express these scores in standardized units (z-scores).[4]

[3] Hourly wages were reported directly by respondents or inferred by NLS staff based on respondent's total compensation, time unit of pay, and total hours, and correspond to their primary (or "CPS") job. Hourly wage values below \$3 and above \$100 are trimmed into this range, and for the sake of consistency the hourly wage measure is inflated to 2017 dollars and transformed using the inverse hyperbolic sine function.

[4] Altonji, Bharadwaj, & Lange (2012) develop a detailed methodology for making AFQT scores comparable across the NLSY-79 and NLSY-97; their methodology accounts for pencil-paper versus computer-based testing formats across the two surveys and other factors, in addition to age-at-testing adjustments. Because the current study is primarily concerned with the extent to which test scores can explain racial earnings differences *within* a generation, while Altonji, Bharadwaj, & Lange are primarily concerned with estimating how the characteristics of youth changed across the cohorts represented in the two surveys, I do not apply a comparable adjustment and instead use the age-adjusted AFQT scores provided directly by the NLSY survey administrators.

No standardized tests were administered to NLS-OC participants directly by the NLS survey enumerators. However, the high schools attended by NLS-OC participants were surveyed in 1968, and among other items these school surveys collected the results of any available standardized tests taken by survey participants. Of the 4,007 NLS-OC participants for whom standardized test scores were sought, their secondary schools were able to provide scores for 3,375 young men, a response rate of 84%.[5] Data on more than 30 different standardized tests was collected, with the most common specific tests being the Otis/Beta/Gamma Test (848 respondents), the California Test of Mental Maturity (625 respondents), the Preliminary Scholastic Aptitude Test (223 respondents), and the Henmon-Nelson Test (216 respondents). Working with NLS administrators, Herriott & Kohen (1973) then collected information on the means and standard deviations of each test from the tests' publishers and used these moments to convert the raw scores from the school survey onto a common scale.

An obvious potential issue is that the test scores available in the NLS-OC are measured with substantial error or are sufficiently different from those available in the later surveys that comparisons across the data sets are uninformative or even misleading. One relatively direct assessment of the comparability of the test-score measures across the three surveys is made possible by the fact that in 1980 the NLSY-79 also conducted a survey of the secondary institutions attended by its participants, and it collected scores on various standardized tests for a subset of NLSY-79 participants. This allows for a direct comparison of AFQT scores and school-survey-derived test scores within a common sample. In Section 2.3, below, I show that if the test-score coefficients in the NLS-OC are scaled by a first-stage regression of school-survey-derived test scores onto AFQT scores estimated with NLSY-79 data, the study's main findings are not qualitatively changed.[6]

[5]The full NLS-OC Young Men's sample contained 5,225 respondents, but test scores were only sought for 4,007 men, with a large majority of these exclusions being young men who had not yet completed ninth grade at the time of the school survey.

[6]In addition to these assessments, Herriott & Kohen (1973) discuss at length the validity of pooling disparate test measures in the NLS-OC, including estimating whether the associations between test performance and parental education and occupation vary across different tests. The authors find that socioeconomic background has similar effects on test performance across the available test types, and they conclude that

Another potentially important issue arises from the fact that the NLS-OC collected test scores from the high schools attended by respondents, so that data on test performance is uniformly missing for respondents whose educational attainment did not advance beyond primary school. Failing to reach high school is relatively rare, with only 6 percent of the working NLS-OC sample having completed eight or fewer years of education. But because it was more common among Black respondents, excluding respondents without test scores decreases the measured Black-white gap in years of completed education. In Section 2.3, I report results that adjust for the effects of truncating the NLS-OC sample in this way, and I show that the study's main findings are again not qualitatively changed.

The educational attainment of each respondent is measured using that respondent's highest grade completed at the time of each survey wave, and in some specifications is recoded into categorical measures.[7] I also create indicators for being incarcerated, being unemployed, and being out of the labor force, with these variables measured at the time of each survey.[8]

"we see little reason for social scientists . . . to be reluctant to pool data from different commonly used tests of mental ability." I also note that several prior studies have compared the effects of the test-score measures from the NLS-OC with those in the later NLSY surveys, including Cunha & Heckman (2016) and Bacolod & Hotz (2006).

[7] The NLS-OC did not collect data on degree completion, and so to maximize comparability across surveys I base the education variables for all three surveys on continuous highest-grade-completed measures.

[8] Incarceration status is determined in slightly different ways in each survey. The NLSY-97 contains the most comprehensive incarceration information, with a monthly array of incarceration status dating to before the survey itself began; the NLSY-79 interviewed incarcerated participants and contains a variable indicating whether the respondent's current residence was in a correctional facility; finally, the NLSY-OC did not attempt to interview incarcerated members but did list incarceration as one of the reasons for noninterview. Labor force status was recorded in all three surveys, typically in a manner similar to the CPS, but was not included in two of the utilized waves of the NLSY-79, leading to modest reductions in sample sizes when analyzing these outcomes.

2 Human Capital and Black-White Differences in Total Earnings

2.1 Main Findings

The basic empirical exercise is to compare the magnitude of the unconditional Black-white earnings gap with the magnitude of the earnings gap conditional on human capital characteristics. I specifically estimate regressions of the following form separately in the NLS-OC, NLSY-79, and NLSY-97 samples:

$$Earnings_i = \alpha + \beta_1 Black_i + X_i\delta + \varepsilon_i \ , \ (1)$$

where $Earnings_i$ is the labor market earnings of individual i, $Black_i$ is an indicator for whether individual i is Black rather than white, and X_i is a vector of individual-level controls. In the baseline estimates of Equation (1), the control vector is empty, while in later specifications it contains human capital controls.[9] I first present estimates using total earnings with zeros *included*, which I consider to be the most comprehensive measure of labor market success and economic well-being. Later I report estimates with alternative dependent variables that focus on specific earnings margins.

The baseline unconditional estimates for total earnings are reported for each of the three data sets in columns 1, 3, and 5 of Table 1. The results indicate that the unadjusted Black-white earnings differential was 91.5 log points in the NLS-OC sample, grew to 146.2 log points in the NLSY-79 sample, and grew further to 197.4 log points in the NLSY-97 sample.

Next, I add controls for standardized test scores and educational attainment to the X_i vector. For simplicity's sake, educational attainment and test scores are entered linearly and are respectively measured in years and in standard deviation units, while in Section 2.2 I show that the results are very similar if less restrictive functional forms are used. Adding

[9]Hispanics and non-Black racial minorities are excluded from all samples.

these covariates refines the earnings comparisons to Black and white men with similar levels of observable human capital, and therefore any attenuation in the Black indicator provides a descriptive estimate for how much of the Black-white earnings gap is attributable to human capital differences.

The conditional estimates are reported in columns 2, 4, and 6 of Table 1, and the levels and percentage changes in the Black coefficient after controlling for human capital are reported in the bottom two rows of the table. Unsurprisingly, controlling for human capital reduces the estimated Black-white earnings gap in all three data sets. More notably, the magnitude of the declines in β_1 that occur after conditioning on education and test scores grows over time. In the NLS-OC, controlling for human capital characteristics decreases the estimated racial earnings gap from 0.915 to 0.804, a decrease of 11 log points, or 12 percent. In the NLSY-79, adding the same controls decreases the estimated gap from 1.462 to 1.183, a decrease of 28 log points, or 19 percent. Finally, in the NLSY-97, the controls for education and standardized test scores reduce the Black-white earnings differential from 1.974 to 1.420, a decrease of 55 log points, or 28 percent.

While these results suggest that the overall contribution of human capital to Black-white differences in total earnings has grown substantially over time, they do not readily differentiate the impact of educational attainment versus standardized test scores. This distinction is nontrivial, since some influential prior studies, most notably Neal & Johnson (1996), have found that performance on standardized tests rather than educational attainment is by far the dominant factor in explaining racial wage differences.[10] One common practice for attempting to determine which specific control variables are driving attenuation in an independent variable of interest is to add the covariates sequentially, but the findings of such an exercise will be dependent on the order in which the covariates are added, and this choice is arbitrary in most applications, including the current one.[11]

[10]Other studies finding that test performance strongly outweighs formal schooling include Fryer (2011) and Luo (2020).

[11]Indeed Lang & Manove (2011) show that controlling for education in a model that already conditions on test scores actually increases the estimated Black-white wage gap. This occurs because, conditional on test scores, Black men actually obtain substantially more education than white men. See Lang & Manove

As an alternative, I implement the decomposition method proposed by Gelbach (2016), which is based on the common practice of adding sets of control variables to a baseline regression and observing any attenuation in a coefficient of interest; however, it allows for the contribution of each specific control variable to be estimated in a manner that is invariant to the order in which the covariates are added. In particular, Gelbach shows that the contribution of a particular covariate to the reduction in a coefficient of interest will be equal to the product of two easily estimable parameters. First is the covariate's coefficient in the model with the full control vector, which in the current application is the coefficient on test scores or education, as reported in Table 1. This parameter provides an estimate of the covariate's association with the dependent variable, conditional on all other covariates. Second is the coefficient on the independent variable of interest in an auxiliary regression of the covariate onto the independent variable of interest. In the current application, these are regressions of test scores and education onto a Black indicator, and therefore they estimate the Black-white gap in these characteristics.[12] The contribution of each covariate is simply the product of these two parameters, and the Gelbach decomposition therefore formalizes the intuition that the extent to which test scores or educational attainment can "explain" Black-white earnings differences depends jointly on their conditional associations with earnings *and* on how strongly they differ by race. Because the *conditional* effect of each covariate is used in this decomposition, the results do not depend on the arbitrary choice of which covariates are added first.

The first key set of parameters for the Gelbach (2016) decomposition, the conditional returns to test scores and educational attainment, was already reported in columns 2, 4, and 6 of Table 1. These estimates indicate that the returns to both standardized test scores and formal schooling increased substantially across the three data sets, consistent with a large existing literature on increases in skill prices in recent decades. Specifically, within the NLS-OC, an additional year of schooling was conditionally associated with a 6.9 log-point

(2011) and Gelbach (2016) for detailed discussions.

[12] Gelbach shows that the estimated contribution of each covariate calculated in this fashion will sum to the total reduction in the coefficient of interest as an identity, and it derives standard error formulas.

increase in total earnings, while this association grew to 13.9 log points in the NLSY-79 and to 19.1 log points in the NLSY-97. Similarly, a standard deviation increase in standardized test performance was conditionally associated with a 3.9 log-point increase in earnings in the NLS-OC sample, while this association grew to 15.9 log points in the NLSY-79 and to 41 log points in the NLSY-97.

The second set of key parameters for the decomposition are the racial gaps in each human capital characteristic, which are estimated with supplemental regressions of each characteristic onto a Black indicator and the baseline control vector. Results of these regressions are reported in Table 2 and, in contrast to the rapidly increasing returns to human capital, show that Black-white differences in human capital were relatively stable across the three surveys. Specifically, columns 1–3 of Table 2 show that the racial gap in years of education fell from 1.03 to 0.81 years between the NLS-OC and the NLSY-79, then grew to 1.12 years in the NLSY-97. Likewise, columns 4–6 of Table 2 estimate that the Black-white gap in standardized test scores was 1.0 standard deviations in the NLS-OC, was virtually unchanged at 1.05 standard deviations in the NLSY-79, then closed moderately to 0.83 standard deviations in the NLSY-97.

These Black-white disparities in human capital are generally consistent with existing estimates from more authoritative data sources. For instance, while we lack standardized national data on test score gaps reaching back to the period covered by the NLS-OC, the test score gap among 17-year-olds taking the National Assessment of Educational Progress mathematics test was approximately 1.18 in 1978 and then fell to 0.96 in 1996.[13] Similarly, Black-white gaps in years of educational attainment in the decennial census show a gap of 0.92 years for census respondents from the same cohorts as the NLSY-79 sample, and a gap of 0.95 years for census respondents from the same cohorts as the NLSY-97 sample. The one estimate from Table 1 that does not closely adhere to patterns in other data sources is the 1.03-year gap in educational attainment in the NLS-OC, which is substantially smaller than in other data sets and likely underestimates the true Black-white education gap for these

[13] Mathematics scores retrieved from nces.ed.gov/nationsreportcard/data/ on 12/19/2020.

cohorts. As noted in Section 1, this is likely due to the mechanical exclusion of NLS-OC respondents who did not reach high school. For the sake of consistency, I first report baseline decomposition results that use the 1.03-year education gap in my actual working NLS-OC sample; then in Section 2.3 I report adjusted results that use Black-white education gaps in line with consensus estimates, which lead to qualitatively similar conclusions.

Table 3 combines the estimated returns to human capital with the estimated size of human-capital gaps and reports full decomposition results for each survey. Column 1 of Table 3 shows that in the NLS-OC, the 11 log-point overall reduction in the earnings gap that occurred after controlling for human capital was about equally attributable to education (7 log points) and standardized test scores (4 log points). Column 2 shows that in the NLSY-79 there was a much larger total reduction of 28 log points and that the contribution of education increased moderately to 11 log points, while the contribution of test scores increased substantially to 17 log points. Finally, Column 3 shows that the total explanatory power of human capital grew even further, to 0.55 log points in the NLSY-97, and that these more recent increases were driven by the increasing importance of both education and test scores. Specifically, the estimated reduction in the total earnings gap due to educational attainment grew to 21 log points (an increase of 10 relative to the NLSY-79), while the estimated reduction due to test scores grew to 34 log points (an increase of 17 relative to the NLSY-79).

On balance, the results in Tables 1 through 3 indicate that while the explanatory power of human capital increased substantially over time, this was almost entirely due to growth in the returns to human capital characteristics, which led racial differences in these characteristics to be increasingly consequential even though the gaps themselves were relatively stable. Indeed, had the association between human capital and earnings remained at the levels that are observed among NLS-OC respondents, who were working in the late 1960s and the 1970s, then the total explanatory power of test scores and education would have actually fallen slightly over time.

The detailed decomposition results also show that while test scores have had somewhat more explanatory power than educational attainment since the 1980s, prior to 1980 the contributions of test scores and educational attainment were approximately equal, and in all three periods both education and test scores have been important contributors to racial earnings gaps. This contrasts with some earlier work that assigned a dominant role to test scores (Neal & Johnson 1996; Fryer 2011).

2.2 Robustness

There are numerous alternatives to the basic modeling choices made in the baseline specifications, and Figure 2 demonstrates the robustness of the key patterns to alternative modeling choices.

I demonstrate robustness to four aspects of model selection. First are sample restrictions. In the baseline specifications, I restricted the sample to men aged 21–37 and excluded current students. However, reasonable alternatives include using a minimum age of 25 to focus on an age range more representative of lifetime earnings, using a maximum age of 32 (since the youngest NLSY-97 respondents were 32 at the time of the most recent survey), and expanding the sample to include current students. Second is the functional form, in which for the human-capital measures the linear variables could reasonably be replaced by sets of dummies for total years of education completed and standardized test-score quartile. Alternatively, total earnings could be transferred as the natural log of total earnings plus one, rather than with the inverse hyperbolic sine function, and still retain zero earners. Third is the inclusion of baseline covariates, for which the specifications above did not include any independent variables beyond race indicators and human capital measures. However, the estimates may be more precise or stable when applying a vector of baseline controls; one reasonable choice of baseline covariates would include age indicators, a south indicator, and an urban residence indicator. Fourth is the application of sampling weights, for which, especially in the NLS-OC, the quality of these weights is unclear, and an alternative is to estimate unweighted models.

Taking all possible permutations of these alternative modeling choices generates 128 possible specifications, and Figure 2 reports the baseline results as well as the 127 alternative models in graphical form.

Specifically, Panel A of Figure 2 shows the reduction in the Black-white earnings gap that occurs after controlling for human capital in each of the three data sets. The reductions reported in Table 1 are shown with a bold line, while the 127 alternatives are shown with light gray lines. The figure shows that the magnitude of the reduction from controlling for human capital grows across the surveys in all of the alternative specifications, and also that none of the baseline results reported in Table 1 were outliers relative to the parameters generated by the full set of alternative modeling choices.

Panels B and C of Figure 2 conduct a similar exercise for the other key pattern from Table 1, the increasing returns to human capital across the three data sets. Specifically, Panel B plots the coefficients on the educational attainment variable, while Panel C plots the coefficients on the standardized test-score variable.[14] Panel B shows that the returns to formal schooling were uniformly increasing across alternative specifications, and that the coefficients on educational attainment in the baseline results from Table 1 were quite typical. The results for standardized test scores that are shown in Panel C are somewhat more variable than those for educational attainment, and in 10 of the 64 models they actually show a small decline in the returns to test scores between the NLSY-79 and the NLSY-97.[15] However, the overall pattern is clearly one of increasing returns to test performance, and the baseline estimates from Table 1 are not outliers compared to the full set of alternative specifications.

[14]Panels B and C necessarily exclude the alternative specifications with nonlinear measures of education and test performance, so that there are 64 possible models rather than 128.

[15]Eight of the ten specifications with declining returns to test performance include current students in the sample, and so may reflect men with higher test scores staying in school further into the life cycle in the NLSY-97 than in the NLSY-79.

2.3 Adjusted Results for the NLS-OC

As discussed in Section 1, there are two important data-quality issues with the NLS-OC sample: 1) potential mismeasurement of standardized test performance and 2) the exclusion of NLS-OC respondents who did not reach high school, which occurs mechanically because these respondents universally lack valid test-score data. In Table 4, I report results that attempt to make reasonable adjustments for both of these issues and gauge whether they change the main conclusions from Tables 1 through 3.

In column 1 of Table 4, I report a coefficient for test scores in the NLS-OC that adjusts for measurement error. Specifically, as noted in Section 1, the NLSY-79 also conducted a survey of the secondary institutions attended by its respondents, and it collected scores on various standardized tests in a manner similar to the test-score collection approach used in the NLS-OC. Since the NLSY-79 also administered the AFQT directly to respondents, I am able to estimate a first-stage regression of AFQT scores onto test scores collected from high schools, and this first-stage estimate is equal to 0.703. The test-score coefficient in column 1 of Table 4 simply scales the baseline NLS-OC test score coefficient (0.039) by the first-stage estimate (0.703), resulting in an adjusted test score coefficient of 0.056. For reference, column 1 of Table 4 also reproduces the coefficient on educational attainment from the NLS-OC.

In column 2 of Table 4, I report the Black-white gap in years of education from the NLS-OC when respondents without valid test-score observations are included, and the estimated gap in this sample is 1.69 years. This is substantially larger than the 1.08-year gap that was reported in Table 2 for the baseline NLS-OC sample, which excluded respondents with missing test-score data, and is more similar to the 1.48-year gap observed among decennial census respondents from the 1941–1952 birth cohorts. Again for reference, column 2 reproduces the estimated Black-white gap in test scores from the NLS-OC.

Column 3 of Table 4 multiplies the human-capital coefficients from column 1 by the human-capital gaps from column 2 to estimate that portion of the Black-white earnings gap attributable to each human-capital characteristic. When using the adjusted figures from columns 1 and 2, the estimated contribution of educational attainment to the Black-white earnings gap in the NLS-OC is –0.117, while the estimated contribution of test scores is –0.056. These estimates are substantively larger than the analogous baseline estimates of –0.07 and –0.04 from Table 3, and the combined contribution of both human-capital characteristics when using the adjusted estimates (–0.173) is also nontrivially larger than the baseline total (–0.111).

These differences suggest that the lower data quality of the NLS-OC likely does have some impact on the estimates. However, even using the adjusted NLS-OC estimates from Table 4, the total explanatory power of human capital in the NLS-OC (17 log points) is still much smaller than the analogous estimate for the NLSY-79 (28 log points) and for the NLSY-97 (55 log points). The fundamental reason that the qualitative patterns across samples are unchanged, even when the estimated contribution of human capital in the NLS-OC increases in the adjusted estimates, is that the growth in the returns to education and test scores across the three surveys is *very* strong. The strength of the growth in skill prices makes it so that in practice, the basic conclusion that human capital accounts for a growing share of Black-white earnings differentials will hold even in the presence of nontrivial bias in all of the relevant parameter estimates.

2.4 Earnings Differences on Extensive and Intensive Margins

Because the estimates in Table 1 retained zero-earners, they encompass both an extensive margin between work and nonwork and an intensive margin of total earnings conditional on working, which in turn depends on hourly wages and total hours worked. Furthermore, there are several distinct reasons men may have zero earnings, including incarceration, unemployment, and labor force withdrawal. Several previous studies have emphasized the importance of accounting for racial differences in nonparticipation specifically when evaluating racial earnings differences (Heckman, Lyons & Todd 2000; Chandra 2000; Juhn 2003), and the relative importance of these different margins is clearly essential for fully characterizing changes in the contribution of human capital to racial earnings differentials. As such, Tables 5 and 6 present additional estimates that help to identify which margins are most important for the observed patterns in total earnings.

Panel A of Table 5 first reports a set of conditional and unconditional specifications similar to those in Table 1, but that use an indicator of having positive earnings as the dependent variable rather than total earnings, and therefore directly assess the extensive margin between work and nonwork. The basic patterns closely mirror those in Table 1 for total earnings, with rapidly growing unconditional Black-white differences in nonwork across the three samples, and with human capital "explaining" a progressively larger share of these gaps. Specifically, in the NLS-OC there is a relatively modest 4.6 percentage point unconditional Black-white gap in having nonzero earnings, which is virtually unchanged at 4.5 percentage points after conditioning on education and test scores. In the NLSY-79, the initial gap in nonwork is 9.2 percentage points, and this gap falls to 8.1 percentage points with the human-capital controls included, a reduction of 1.1 percentage points, or 12 percent. Finally, in the NLSY-97, the unconditional gap in nonzero earnings grows further to 14.6 percentage points, and conditioning on education and test scores reduces this differential to 10.7 percentage points, a decline of 3.9 percentage points, or 27 percent.

Also similar to the total earnings estimates in Table 1, the increasing importance of human capital for explaining Black-white gaps in nonzero earnings primarily reflects increases in the returns to human capital. Specifically, the estimates in Panel A indicate that an additional year of schooling increases the probability of nonzero earnings by a statistically insignificant 0.1 percentage points in the NLS-OC, but this association increases to statistically significant coefficients of 0.6 percentage points in the NLSY-79 and 1.3 percentage points in the NLSY-97. Similarly, a standard-deviation increase in test scores is virtually uncorrelated with the probability of having nonzero earnings in the NLS-OC, but is correlated with a 0.6 percentage point increase in the NLSY-79 and a 3.0 percentage point increase in the NLSY-97.

Panel B of Table 5 reports the results from a similar set of specifications that use hourly wages as the outcome variable. Hourly wages are a key component of total earnings among working men, and the results in Panel B therefore help us assess the contribution of human capital to racial gaps in earnings on the intensive margin. Additionally, hourly wages are a widely used measure in the literature on racial disparities in economic outcomes, so the results in Panel B are useful for comparative purposes.

Panel B shows that the patterns when hourly wages are used as the dependent variable are qualitatively different from those observed when using total earnings or an indicator of positive earnings as the outcome measure. In particular, the estimates in Panel B show that the unconditional Black-white wage gap did not substantively change across the three data sets. The size of the reduction in the Black-white wage gap from controlling for human capital follows an inverted U-shaped pattern: in the NLS-OC, the decrease in the wage gap from controlling for human capital is 8 log points, or 31%; in the NLSY-79, the magnitude of this reduction rises to 12 log points, or 44%; but in the NLSY-97 it falls again to 8 log points, or 37%.[16]

These patterns in hourly wages among working men are, again, primarily driven by changes in the returns to education and test scores: Panel B estimates that the association between an additional year of education and hourly wages increased from 4 log points in the NLS-OC to 6 log points in the NLSY-79, but then remained stagnant at 6 log points in the NLSY-97. Likewise, the association between a standard-deviation increase in test scores and hourly wages increased from 4 log points in the NLS-OC to 7 log points in the NLSY-79, but then decreased to 3 log points in the NLSY-97. These patterns highlight that the widely discussed increases in the return to skill in the late twentieth century and early twenty-first

[16] Neal & Johnson (1996) also use the NLSY-79, and they estimate that controlling for AFQT score reduces the Black-white wage gap from 24.4 log points to 7.2 log points, which is a substantially larger reduction than what is shown in columns 3 and 4 of Panel B. When I imitate Neal & Johnson by restricting the sample to men born after 1961 and observing for wages in 1990 or 1991, as well as by controlling only for AFQT rather than for AFQT and educational attainment simultaneously, I find that the Black-white wage gap falls from 26.1 log points to 11.2 after controlling for test scores, a drop quite similar to that found by Neal & Johnson.

century apply primarily to the extensive margin.[17]

Overall, the results in Table 5 suggest that the growing importance of human capital for explaining Black-white gaps in total earnings occurred primarily at the margin between work and nonwork. Given this, it is useful to distinguish between different reasons for nonwork. Three broad categories of nonwork, all of which have been shown to differ significantly by race, are 1) incarceration, 2) unemployment, and 3) labor force withdrawal. To better understand which types of nonemployment are most relevant, Table 6 estimates conditional and unconditional Black-white gaps in each of these categories across the three surveys, similar to Tables 1 and 5.[18]

The results in Table 6 suggest that human capital has become more important in explaining Black-white gaps in all three forms of nonwork. For instance, with respect to incarceration, controlling for educational attainment and test scores in the NLS-OC does not change the coefficient on the Black indicator, which is just 0.012 in both specifications. But in the NLSY-79, the reduction in the Black-white incarceration gap after controlling for human capital increases to 0.8 percentage points, or 15.2 percent, and in the NLSY-97, human capital again descriptively explains 0.8 percentage points of the racial differential in incarceration rates; because of lower incarceration rates, this differential represents a 25.0 percent decline. Similarly, the reduction in Black-white differences in unemployment, after accounting for human capital differences, increases from 0.1 percentage points (2 percent) in the NLS-OC to 1.7 percentage points (31 percent) in the NLSY-79, to 1.5 percentage points (38 percent) in the NLSY-97. The patterns in Panel C of Table 5 for labor force withdrawal are similar, except that in percentage there is a modest decrease in the explanatory power of human capital between the NLSY-79 and the NLSY-97. (The level changes for labor force withdrawal increase monotonically across the three surveys.)[19]

[17] Castex & Dechter (2014) and Deming (2017) also find that the wage returns to test scores fell in the NLSY-97 versus the NLSY-79.

[18] Individuals who are incarcerated are coded to be neither out of the labor force nor unemployed, so that the three categories of nonwork are mutually exclusive.

[19] The current data measure incarceration contemporaneously, and comprehensive records of past periods of incarceration or other interactions with the criminal justice system are not available in all three surveys. Because criminal convictions and incarceration reduce future employment opportunities (Western 2002;

3 Racial Differences in the Returns to Human Capital

All of the specifications reported above restricted the returns to human capital so that they were equal across racial groups. Table 7 reports the results of specifications that relax this restriction by regressing total earnings onto educational attainment and test scores separately for the Black and white samples from each survey, and therefore allowing the returns to the skill measures to differ by race.

Table 7 indicates that in all three samples, and for both education and test scores, the returns to the skill measures are uniformly larger for Blacks than for whites. For instance, in the NLS-OC sample, a one-year increase in educational attainment is associated with an 18.6 log-point increase in earnings among Blacks and a 6.2 log-point increase in earnings among whites, while in the NLSY-79 sample, the estimated returns to a year of education for Blacks and whites are 44.0 log points and 12.7 log points, respectively, and in the NLSY-97, the estimated returns to a year of education for Blacks and whites are respectively 47.1 and 13.3 log points. Similarly, the earnings increase associated with a one-standard-deviation improvement in test scores is 2.4 log points for Blacks versus 4.2 log points for whites in the NLS-OC, 35.6 log points for Blacks versus 15.9 log points for whites in the NLSY-79, and 80.4 log points for Blacks versus 34 log points for whites in the NLSY-97.

These large differences in the returns to human capital are perhaps surprising, and they have a number of potentially important implications. For instance, they suggest that greater levels of human capital are strongly rewarded among Black men in post–Civil Rights labor markets, or, conversely, that Black men with lower levels of human capital face particularly large earnings penalties.[20] This would imply that racial earnings differentials will be most acute at the lower end of the human capital distribution, which is consistent with evidence from Bayer & Charles (2018).

Neal & Rick 2014), some of the estimated effects for unemployment and labor force withdrawal may partially reflect lagged effects of criminal justice disparities, so that the estimates in Panel A likely understate incarceration's impact on Black-white gaps in nonemployment.

[20] The returns to human capital are greater among Blacks than whites even when the specifications in Table 7 are estimated for respondents living in the South, where more discrimination might be expected, especially in the NLS-OC sample.

While the differential returns to human capital shown in Table 7 are of interest for all of these reasons, a question more specifically relevant to the current paper is how these differential returns affect the conclusion that the contribution of human capital to Black-white gaps in total earnings has grown since the 1960s.

The decompositions estimated above calculated the contribution of human capital to Black-white earnings differences as the joint product of 1) Black-white gaps in human capital and 2) the association between human capital and earnings. This approach is still applicable in a setting where the association between human capital and earnings varies by race, but the estimates will now depend on which set of coefficients for the human-capital characteristics are used. Since this choice is essentially arbitrary, I produce estimates using both the Black and white coefficients and report the results in the bottom row of Table 7. Specifically, I calculate $(\bar{X_w} - \bar{X_b})'\hat{\beta_b}$ as well as $(\bar{X_w} - \bar{X_b})'\hat{\beta_w}$ in each sample, where $\bar{X_w}$ and $\bar{X_b}$ are the means of the human capital characteristics among whites and Blacks, while $\hat{\beta_w}$ and $\hat{\beta_b}$ are vectors of regression coefficients on the human-capital coefficients for whites and Blacks. Note that these quantities are identical to the "explained" portion of a standard Oaxaca-Blinder decomposition, sometimes referred to as "quantities" or "endowment" effects, which estimate how the gap in a given outcome between two groups would change if those groups had the same average levels of a set of covariates.[21]

The results at the bottom of Table 7 show that when using the coefficients among Blacks, the estimated contribution of human capital to the racial earnings gaps increases from 0.217 in the NLS-OC to 0.728 in the NLSY-79, to 1.193 in the NLSY-97. Conversely, when the white human capital coefficients are used, the estimated contribution of human capital to the racial earnings gap increases from 0.106 in the NLS-OC to 0.270 in the NLSY-79, to 0.431 in the NLSY-97. The uniformly larger estimates when using the Black coefficients simply reflect the higher returns to human capital among Blacks as shown in the top of Table 7: if the returns to skill are higher, as they are within the Black sample, then equalizing skill levels

[21] Gelbach (2016) discusses the relationship between his decomposition method and the Oaxaca-Blinder decomposition, showing that a simple extension of the Gelbach decomposition nests the traditional Oaxaca-Blinder decomposition.

would be expected to cause a greater reduction in the earnings gap. Most important for our present purposes, however, is that the estimated contribution of human capital to the Black-white earnings gap grows substantially over time even when allowing the returns to skill to vary by race. This occurs because the returns to human capital increase significantly across the three samples for both Blacks and whites, even though the overall returns to human capital are greater for Blacks. In any setting where the returns to human capital increase while Black-white gaps in human capital remain approximately constant, the contribution of human capital to racial earnings gaps will also increase.

4 Conclusion

Many of the findings presented here are well established in the previous literature. For instance, Chandra (2000), Ritter & Taylor (2011), and Bayer & Charles (2018) all stress the importance of evaluating racial employment gaps in addition to wages, while Castex & Dechter (2014) and Altonji, Bharadwaj, & Lange (2012) investigate changes in the returns to human capital across NLSY surveys. And methodologically, the techniques used to estimate the contribution of human capital to racial disparities in labor market outcomes are very similar to those in Neal & Johnson (1996) and Gelbach (2016), among others.

But while these aspects of my approach and findings are not strictly novel, systematically estimating the contribution of human capital to racial inequality across the full post–Civil Rights period allows for several important insights that were not readily apparent from the existing literature.

First is that the aggregate contribution of human capital to differences in the earnings of Black and white men grew steadily over the past 50 years, and the overall importance of human capital for racial inequality has never been larger than it is today. This basic pattern applies to both formal schooling and to standardized test performance, which likely captures difficult-to-observe aspects of cognitive ability, school quality, and family background. But importantly, these patterns overwhelmingly reflect an increasingly strong relationship between human capital and the avoidance of zero earnings, rather than changing Black-white gaps in human-capital characteristics or increasing returns to human capital on intensive margins like wages.

These findings suggest that the nature of human capital and racial earnings disparities are qualitatively different today from what they were in the immediate aftermath of the Civil Rights Act. In particular, among men engaged with the labor market of the late 1960s and the 1970s, human capital was strongly associated with hourly wages but only weakly associated with having nonzero earnings. As a result, Black men with lower levels of human capital certainly earned less than their white counterparts of similar skill levels, but they were only moderately less likely to be working. This changed dramatically as the latter half of the twentieth century progressed, and now, among men in the contemporary U.S. labor market, human-capital differences between Blacks and whites have become very strongly associated with the probability of working at all. As a result, rather than "only" facing a wage penalty, Black men with lower levels of human capital are now frequently incarcerated, unemployed, or have withdrawn from the labor force during their prime working years.

These qualitative changes mirror key structural developments in the U.S. labor market and U.S. society more generally. These include skill-biased technical change and increasing returns to skill, job polarization and declining male labor-force participation rates, and the rise of mass incarceration. A key finding of the current study is that these developments have dramatically changed the extent and manner in which human capital contributes to racial earnings disparities.

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Figure 1: Black-White Gap in Total Earnings

Census and ACS versus NLS Surveys

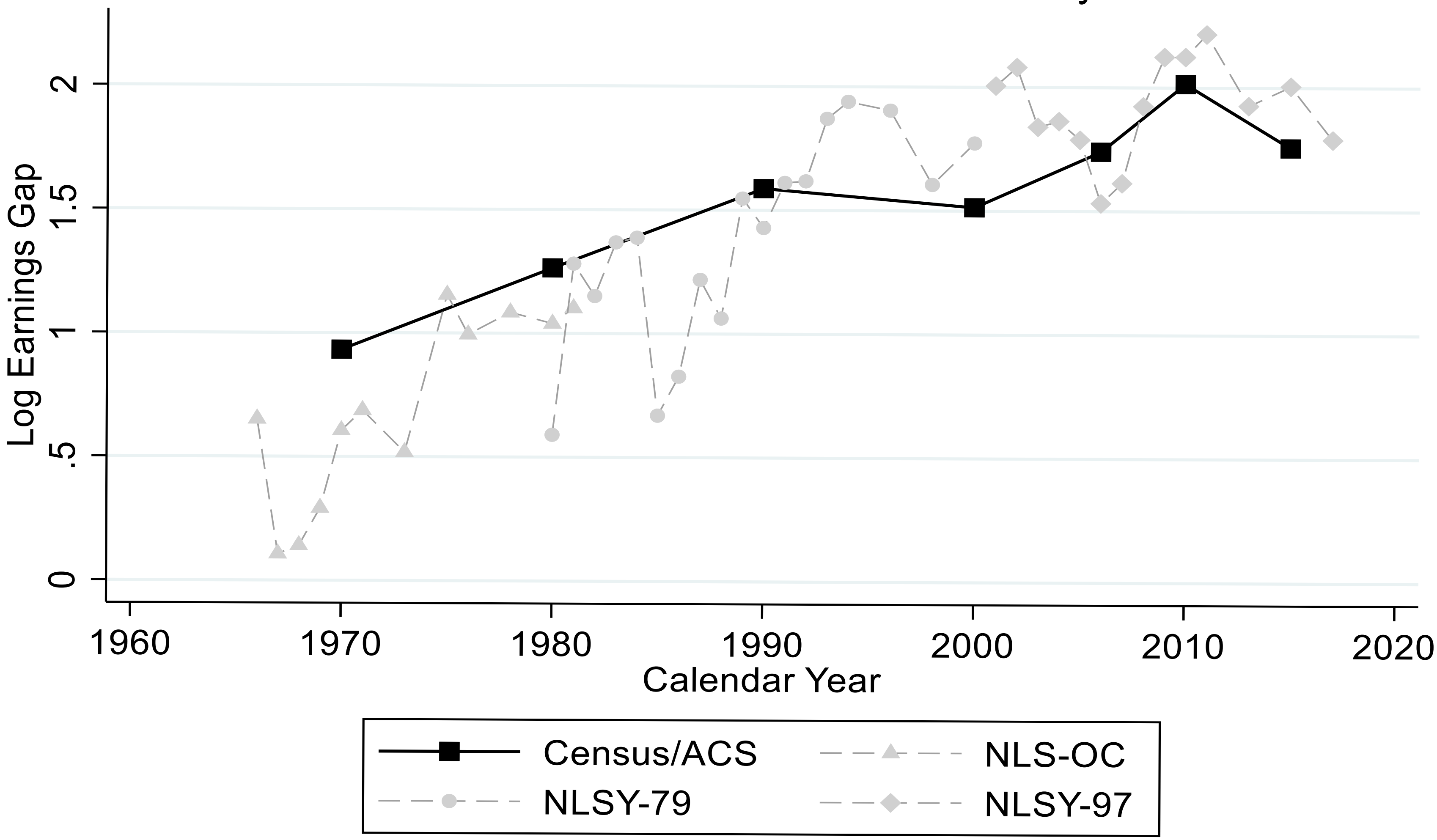

Figure 2: Specification Checks

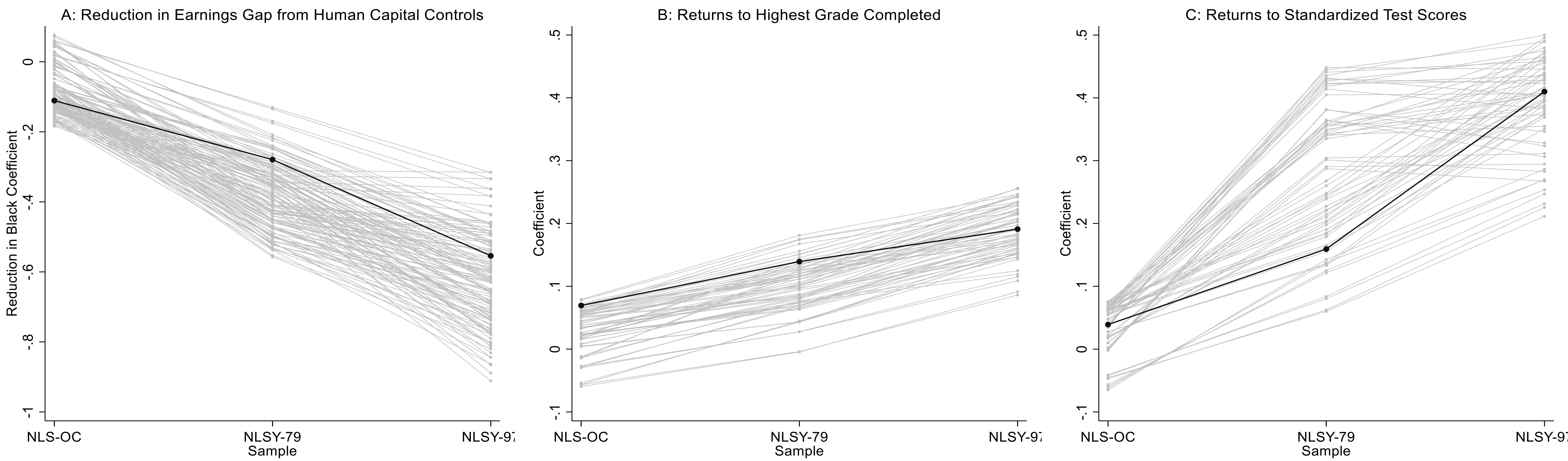

Table 1: Unconditional and Conditional Black-White Earnings Differentials

	(1)	(2)	(3)	(4)	(5)	(6)
	NLS-OC		NLSY-79		NLSY-97	
	Baseline	With Controls	Baseline	With Controls	Baseline	With Controls
Black	-0.915***	-0.804***	-1.462***	-1.183***	-1.974***	-1.420***
	(0.132)	(0.139)	(0.169)	(0.172)	(0.135)	(0.136)
Educational Attainment (years)		0.069***		0.139***		0.191***
		(0.019)		(0.021)		(0.021)
Test Score (standard deviations)		0.039		0.159***		0.410***
		(0.045)		(0.060)		(0.063)
Observations	19,905		35,471		23,660	
Level Change After Covariates	**0.111**		**0.279**		**0.554**	
Percent Change After Covariates	**12.1%**		**19.1%**		**28.1%**	

Notes: The dependent variable for all models is the inverse hyperbolic sine of total earnings, with zeros included. Observations consist of person-years. All samples are restricted to non-Hispanic Black and white men between the ages of 21 and 37 who are not currently enrolled in school. Sampling weights applied. Standard errors are clustered at the individual level and reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2: Black-White Gaps in Human Capital Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Educational Attainment			Test Scores		
	NLS-OC	NSLY-79	NLSY-97	NLS-OC	NSLY-79	NLSY-97
Black	-1.03***	-0.81***	-1.12***	-1.00***	-1.05***	-0.83***
	(0.13)	(0.12)	(0.11)	(0.06)	(0.05)	(0.04)
Observations	19,905	35,471	23,660	19,905	35,471	23,660

Notes: The dependent variable for Columns 1-3 is educational attainment measured in years, while the dependent variable for Columns 4-6 is standardized test scores measured in standard deviations. Observations consist of person-years. All samples are restricted to non-Hispanic Black and white men between the ages of 21 and 37 who are not currently enrolled in school. Sampling weights applied. Standard errors are clustered at the individual level and reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 3: Decomposition of Black-White Gaps in Total Earnings

	NLS-OC	NLSY-79	NLSY-97
Total Gap Attributable to Human Capital	-0.11***	-0.28***	-0.55***
	(0.02)	(0.02)	(0.02)
Attributable to Education	-0.07***	-0.11***	-0.21***
	(0.01)	(0.01)	(0.01)
Attributable to Test Scores	-0.04*	-0.17***	-0.34***
	(0.02)	(0.02)	(0.02)

Notes: Table reports the results of the decomposition procedure described by Gelbach (2016). The first row reports the reduction in the Black coefficient that occurs in each survey after conditioning on educational and test scores, as shown in Table 1. The second and third rows respectively decompose this total reduction into portions attributable to education and test scores. These contributions are calculated as the product of the education (test score) coefficient as reported in Table 1, and the Black-white gap in education (test scores) as reported in Table 2. Observations consist of person-years. All samples are restricted to non-Hispanic Black and white men between the ages of 21 and 37 who are not currently enrolled in school. Sampling weights applied. Standard errors are calculated using the formulas derived in Gelbach (2016) with individual-level clustering and reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4: Adjusted NLS-OC Results

	(1) Adjusted Coefficients	(2) Adjusted Gaps	(3) Adjusted Contributions	(4) Unadjusted Contributions
Educational Attainment (years)	0.069*** (0.019)	-1.69*** (0.139)	-0.117	-0.072
Test Score (standard deviations)	0.056 (0.063)	-1.00*** (0.06)	-0.056	-0.039
	Total Contribution of Human Capital		-0.173	0.111

Notes: This table makes adjustments to account for potential data and measurement issues in the NLS-OC survey. Column 1 of this table reports an adjusted test score coefficient that scales the NLS-OC test score coefficient reported in Table 1 by a first-stage estimate of .704 (the educational attainment coefficient in Column 1 of this table reproduces the baseline estimate from Table 1 for reference). Column 2 of this table reports an adjusted Black-white gap in educational attainment that includes NLS-OC respondents without valid test score data, and given the construction of the NLS-OC sample this includes respondents who did not attend high school (the test score gap reported in Column 2 of this table reproduces the baseline estimate from Table 2 for reference). Column 3 of this table estimates the contribution of education and test scores to the Black-white earnings gap by taking the product of the education/test score coefficients and the Black-white education/test score gaps using the adjusted parameters. Column 4 of this table reproduces the baseline compositions from Table 3 for comparison. Standard errors are clustered at the individual level and reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5: Black-White Earnings Differentials on the Extensive and Intensive Margin

Panel A: Indicator of Positive Earnings

	NLS-OC		NLSY-79		NLSY-97	
	Baseline	With Controls	Baseline	With Controls	Baseline	With Controls
Black	-0.046***	-0.045***	-0.092***	-0.081***	-0.146***	-0.107***
	(0.011)	(0.012)	(0.014)	(0.015)	(0.011)	(0.012)
Educational Attainment (years)		0.001		0.006***		0.013***
		(0.002)		(0.002)		(0.002)
Test Score (standard deviations)		-0.000		0.006		0.030***
		(0.003)		(0.005)		(0.005)
Observations	19,835		35,471		23,854	
Level Change After Covariates	**0.001**		**0.011**		**0.039**	
Percent Change After Covariates	**2.2%**		**12.0%**		**26.7%**	

Panel B: Hourly Wages

	NLS-OC		NLSY-79		NLSY-97	
	Baseline	With Controls	Baseline	With Controls	Baseline	With Controls
Black	-0.260***	-0.180***	-0.269***	-0.150***	-0.213***	-0.134***
	(0.022)	(0.022)	(0.024)	(0.023)	(0.021)	(0.022)
Educational Attainment (years)		0.040***		0.060***		0.062***
		(0.004)		(0.004)		(0.004)
Test Score (standard deviations)		0.039***		0.074***		0.026**
		(0.009)		(0.011)		(0.012)
Observations	17,200		32,498		20,540	
Level Change After Covariates	**0.080**		**0.119**		**0.079**	
Percent Change After Covariates	**30.8%**		**44.2%**		**37.1%**	

Notes: The dependent variable is indicated in the subtitle for each panel. Observations consist of person-years. All samples are restricted to non-Hispanic Black and white men between the ages of 21 and 37 who are not currently enrolled in school. Samples in Panel B are further restricted to working men with valid hourly wage data. Sampling weights applied. Standard errors are clustered at the individual level and reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 6: Black-White Gaps in Different Categories of Non-Work

	NLS-OC		NLSY-79		NLSY-97	
	Baseline	With Controls	Baseline	With Controls	Baseline	With Controls
Panel A: Incarcerated						
Black	0.012***	0.012***	0.052***	0.044***	0.031***	0.023***
	(0.003)	(0.003)	(0.009)	(0.009)	(0.005)	(0.005)
Educational Attainment (years)		-0.001***		-0.002***		-0.005***
		(0.000)		(0.000)		(0.001)
Test Score (standard deviations)		0.001		-0.006***		-0.003*
		(0.001)		(0.002)		(0.002)
Observations	17,744		34,176		23,990	
Level Change After Covariates	**0.0000**		**0.0079**		**0.0079**	
Percent Change After Covariates	**-0.2%**		**15.2%**		**25.8%**	
Panel B: Unemployed						
Black	0.057***	0.056***	0.056***	0.038***	0.039***	0.024***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.005)	(0.005)
Educational Attainment (years)		-0.002***		-0.007***		-0.005***
		(0.001)		(0.001)		(0.001)
Test Score (standard deviations)		0.001		-0.011***		-0.010***
		(0.002)		(0.003)		(0.002)
Observations	20,083		35,515		23,341	
Level Change After Covariates	**0.001**		**0.017**		**0.015**	
Percent Change After Covariates	**2.0%**		**31.3%**		**37.8%**	
Panel C: Out of Labor Force						
Black	0.033***	0.034***	0.041***	0.021**	0.090***	0.066***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Educational Attainment (years)		-0.006***		-0.002**		-0.011***
		(0.001)		(0.001)		(0.002)
Test Score (standard deviations)		0.007**		-0.018***		-0.014***
		(0.003)		(0.003)		(0.005)
Observations	20,083		35,515		23,341	
Level Change After Covariates	**-0.001**		**0.021**		**0.024**	
Percent Change After Covariates	**-2.2%**		**49.6%**		**26.6%**	

Notes: The dependent variable is indicated in the subtitle for each panel. Observations consist of person-years. All samples are restricted to non-Hispanic Black and white men between the ages of 21 and 37 who are not currently enrolled in school. Sampling weights applied. Standard errors are clustered at the individual level and reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 7: Differences in the Returns to Human Capital by Race

	(1)	(2)	(3)	(4)	(5)	(6)
	NLS-OC		NLSY-79		NLSY-97	
	Black	White	Black	White	Black	White
Educational Attainment (years)	0.186*	0.062***	0.440***	0.127***	0.471***	0.133***
	(0.103)	(0.018)	(0.086)	(0.022)	(0.048)	(0.023)
Test Score (standard deviations)	0.024	0.042	0.356	0.159***	0.804***	0.340***
	(0.212)	(0.045)	(0.236)	(0.061)	(0.164)	(0.069)
Constant	7.527***	9.912***	3.872***	8.726***	2.882***	8.295***
	(1.478)	(0.253)	(1.254)	(0.284)	(0.662)	(0.318)
Observations	3,019	16,886	3,964	31,507	7,877	15,783
	$(\bar{x}_w - \bar{x}_b)'\hat{B}_b$	$(\bar{x}_w - \bar{x}_b)'\hat{B}_w$	$(\bar{x}_w - \bar{x}_b)'\hat{B}_b$	$(\bar{x}_w - \bar{x}_b)'\hat{B}_w$	$(\bar{x}_w - \bar{x}_b)'\hat{B}_b$	$(\bar{x}_w - \bar{x}_b)'\hat{B}_w$
Estimated Contribution of Human Capital to Earnings Gap ("Explained Component")	.217	.106	.728	.270	1.193	.431

Notes: Column headings indicate the race of the sample used in each model. The dependent variable for all models is the inverse hyperbolic sine of total earnings, with zeros included. Observations consist of person-years. All samples are restricted to men between the ages of 21 and 37 who are not currently enrolled in school. Sampling weights applied. Standard errors are clustered at the individual level and reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.